How can we reduce the CFS systematic errors?

High-resolution ocean model

→ **Strongly coupled data assimilation**

→ **Model bias correction using A-B**

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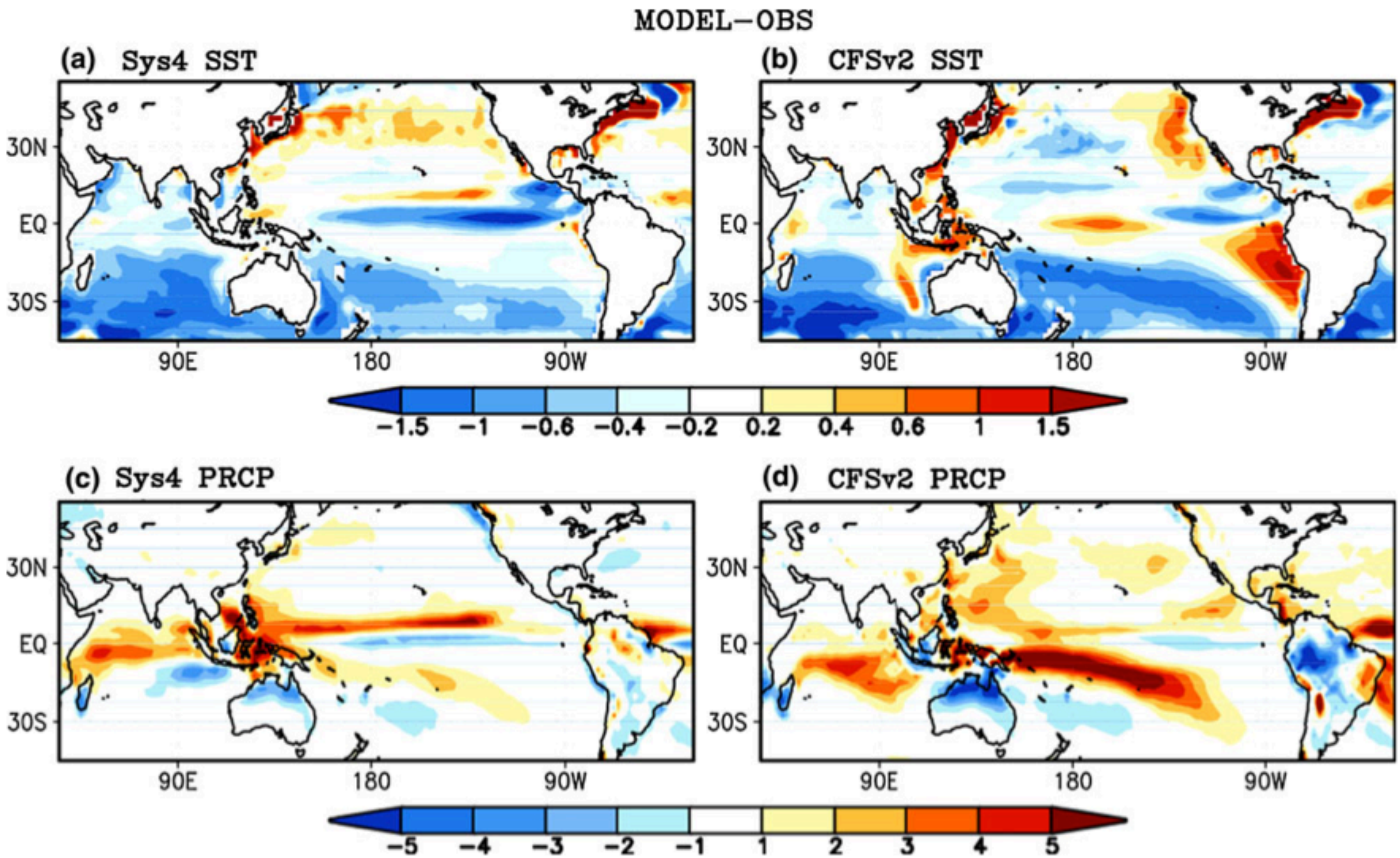
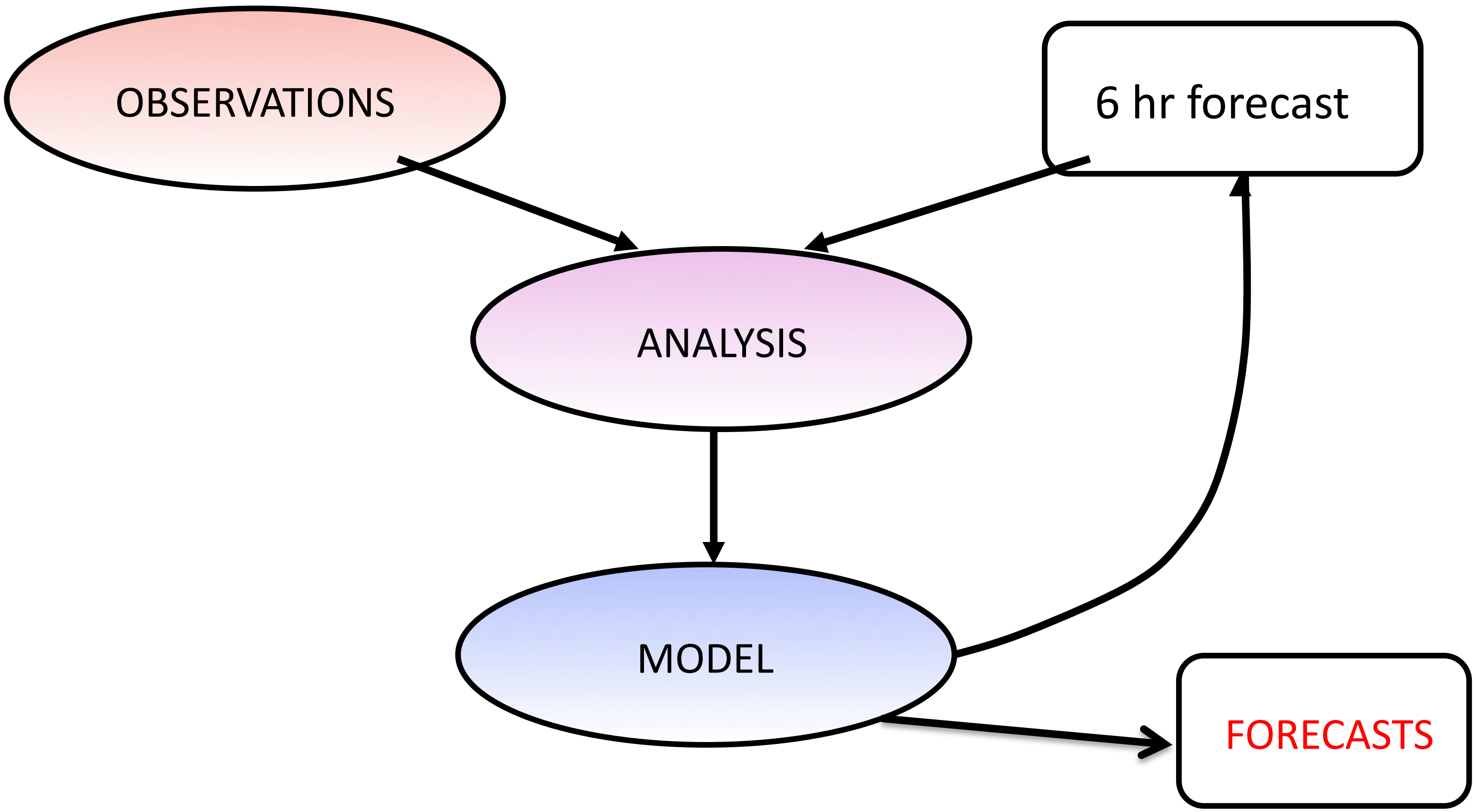
Kim-Webster-Curry (2012) comparison of the bias of the coupled Syst4 (ECMWF) and the CFS-v2 (NCEP)

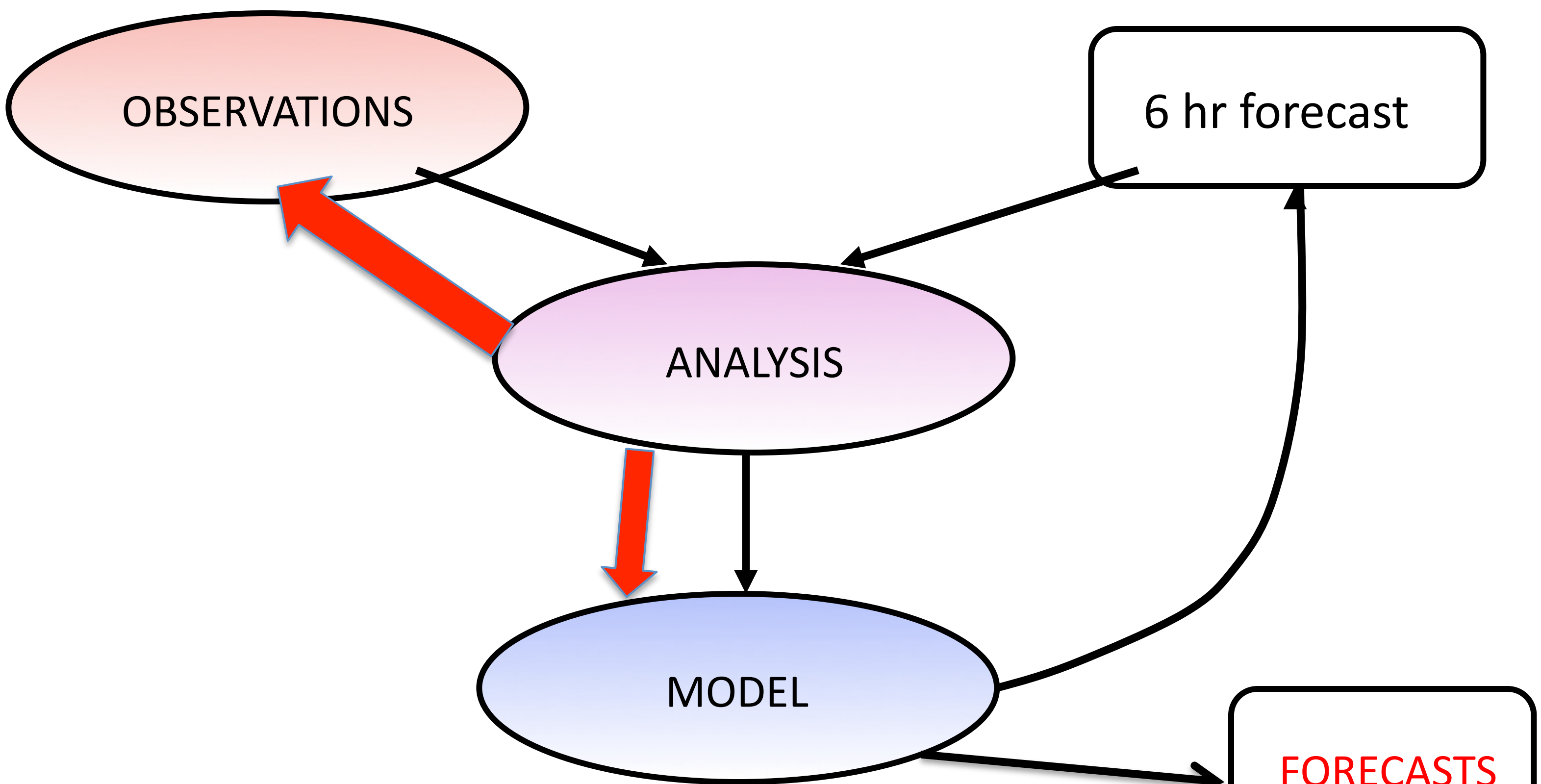


Both models have large biases, but they are also quite similar!

Classic Data Assimilation: For NWP we need to improve observations, analysis scheme and model



New Data Assimilation: We can also use DA to improve observations and model



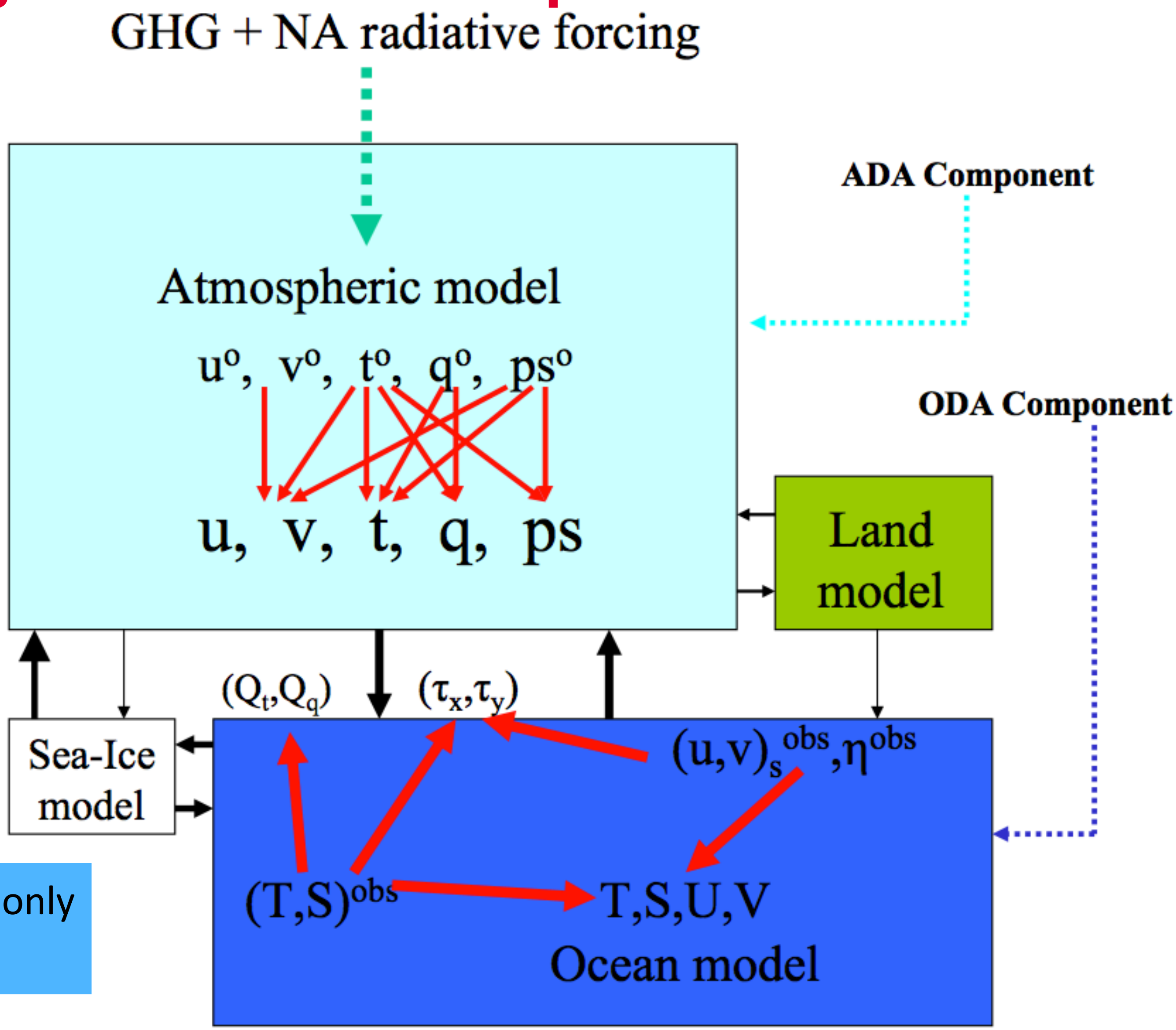
1) How to best do coupled ocean-atmosphere data assimilation?

- Should we do coupled data assimilation?
- Yes! e.g., see Tamara Singleton thesis
- Current approaches assimilate separately the ocean and the atmosphere, and then couple the models (weak coupling)
- We proposed strong coupling: the ocean sees the atmospheric observations, and the atmosphere sees the ocean observations (Sluka, Penny, Miyoshi)

Data Assimilation: STANDARD (WEAK) COUPLING
S. Zhang et al.: GFDL Coupled Ocean-Atm EnKF

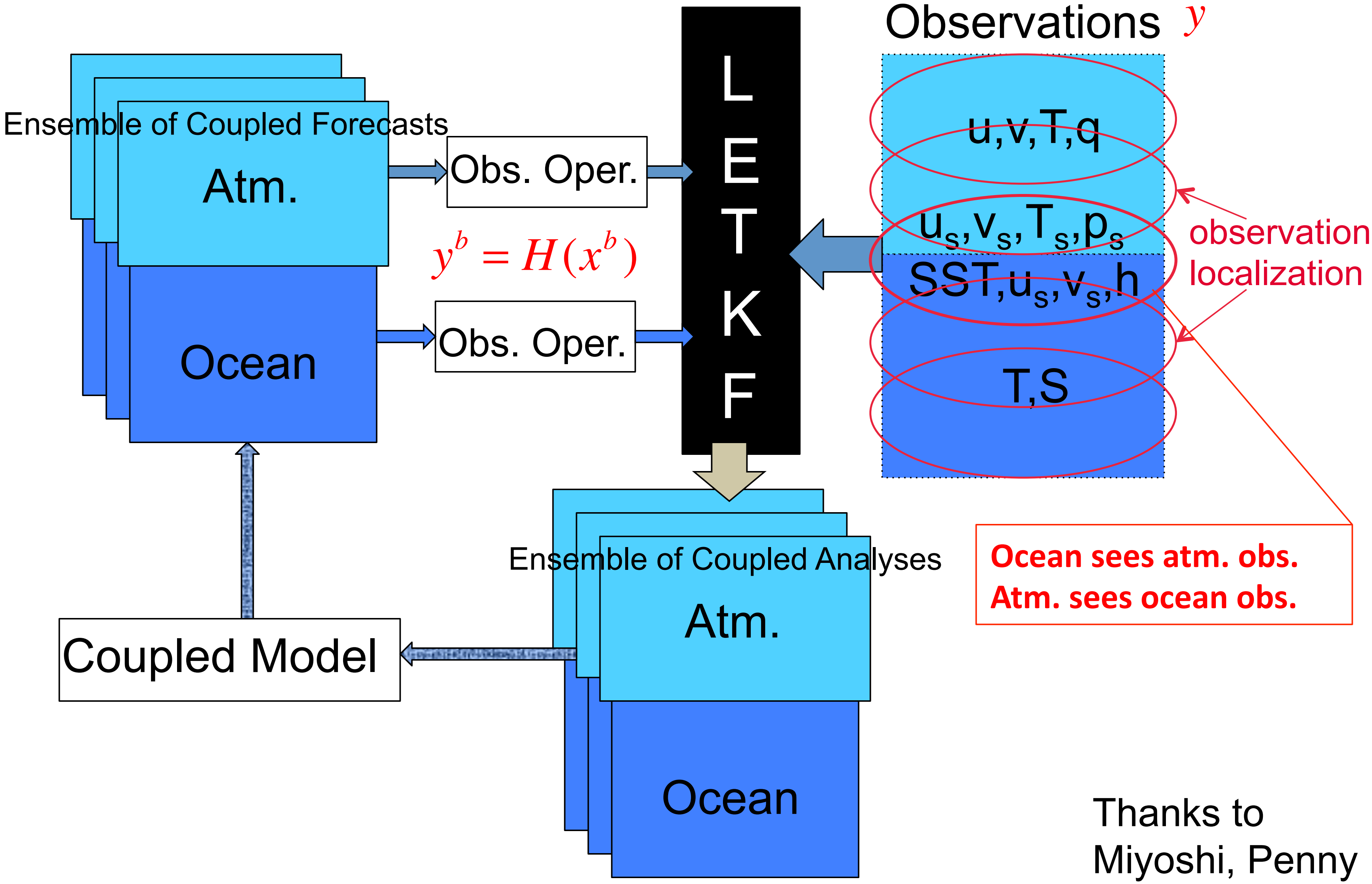
Pioneering!

Atmosphere assimilates only atm. obs.!



Ocean assimilates only ocean obs.!

Our strongly coupled LETKF assimilation



Thanks to
Miyoshi, Penny

Impact of strong coupling of the ocean-atmosphere LETKF (Sluka et al, submitted)

- **SPEEDY-NEMO** coupled model. Perfect model OSSE.
- Standard (weak) coupling as a control
- Test strong coupling: the ocean sees the atmospheric observations and the atmosphere sees the ocean observations

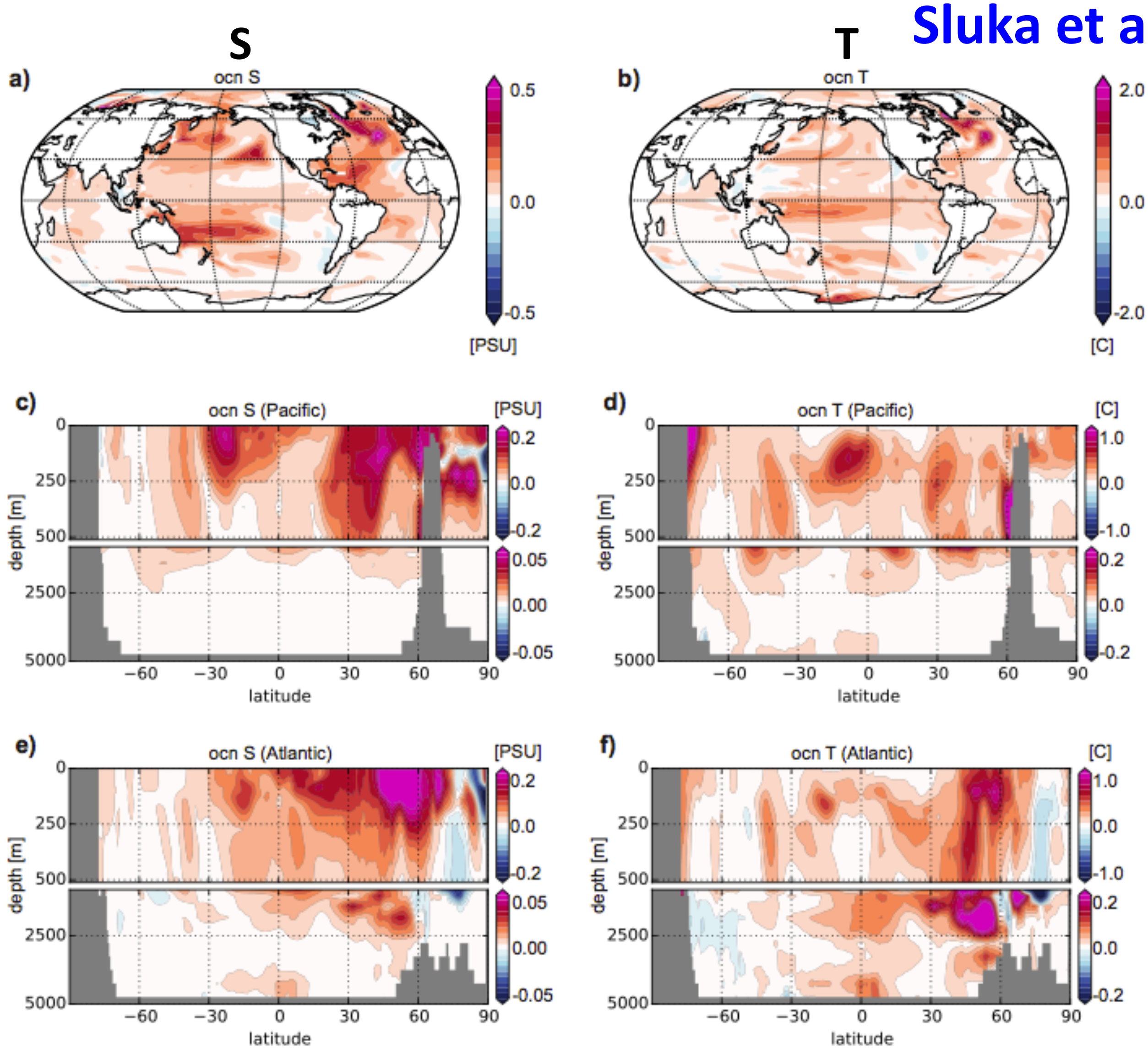
Experiments: 1) Only atmos. obs.

(2) Only ocean obs.)

- CONTROL: Weakly coupled data assimilation: Only the atmosphere assimilates atmos. observations.
- Strongly coupled DA: ocean also assimilates atmospheric observations (and vice versa).

Results: Red means STRONG DA is better!

Sluka et al., under revision GRL

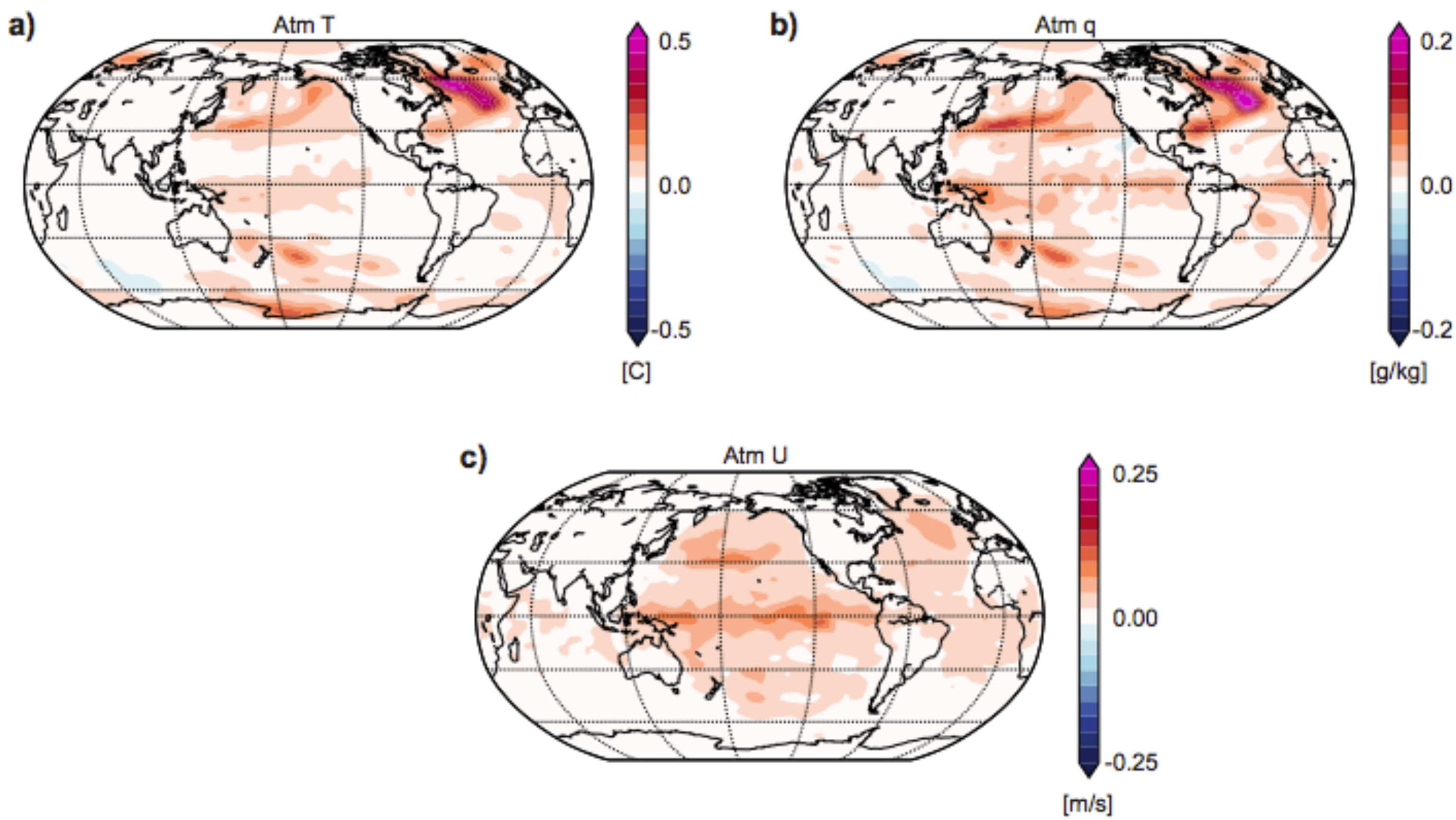


- With Strongly Coupled DA, the errors in temperature and salinity decrease by about 50%.
- The improvements reach the lower levels.

Results: Red means STRONG DA is better!

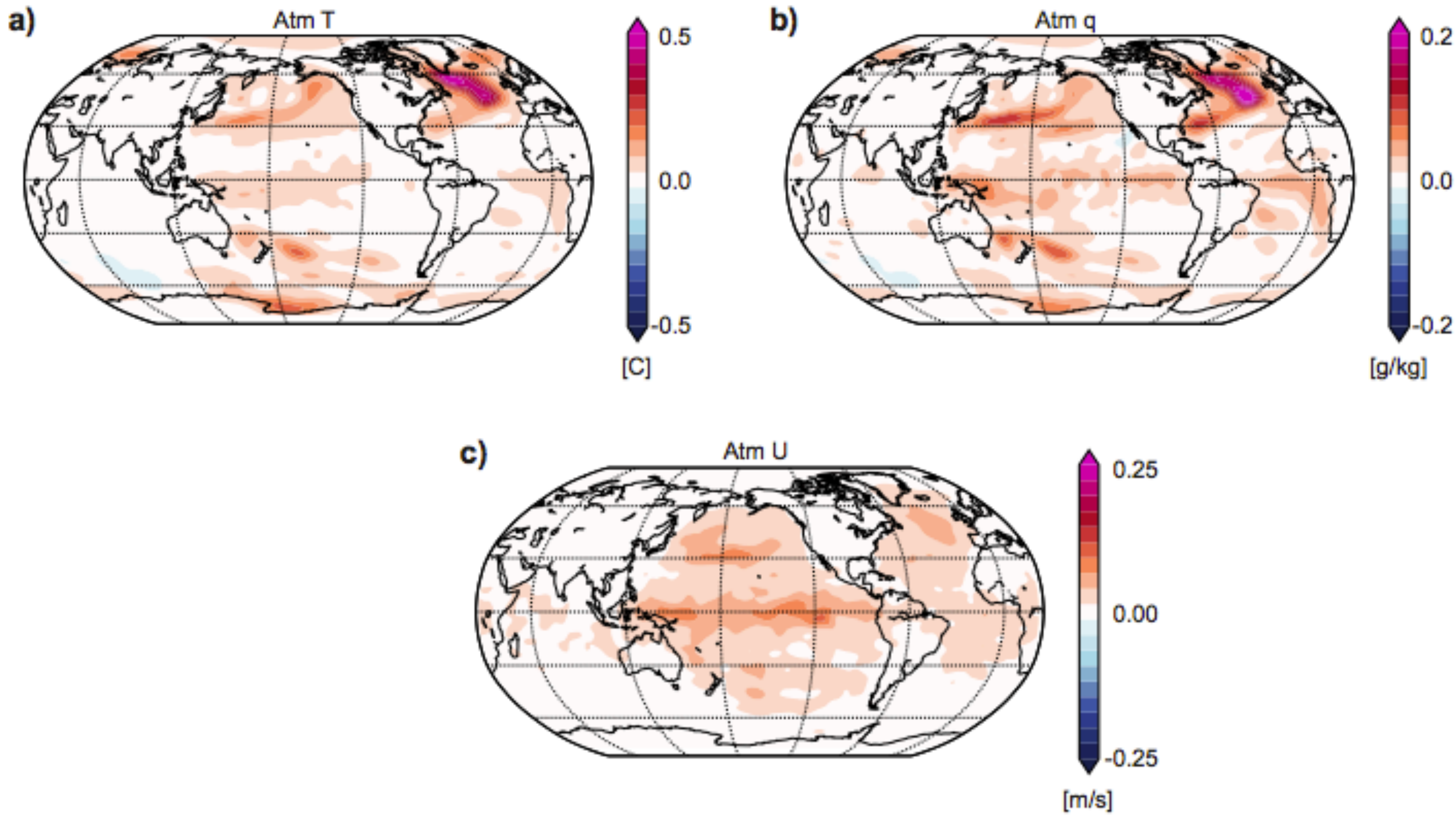
Sluka et al., under revision, GRL

In turn, with Strongly Coupled DA, **the ocean improved by assimilating atmospheric observations improves the atmosphere**!



It’s great that EMC plans to do strongly coupled DA for all models, not just the ocean!

They should improve each other!



How can we estimate and correct model bias?

- The Analysis is the best estimate of the Truth.
- The First Guess (6hr forecast) contains the initial forecast errors (before they grow nonlinearly).
- Analysis - First Guess = Analysis Increments (**AI**) = - Initial (linear) model errors.
- **The time average of AI is the best estimate of the error growth due to model bias in 6 hr.**
- Danforth, Kalnay and Miyoshi (DKM-2007) estimated the 6hr errors of the SPEEDY model.
- Estimated the average SPEEDY model error (bias) by averaging over several years the 6 hour forecast (started from reanalysis R1) minus the reanalysis.

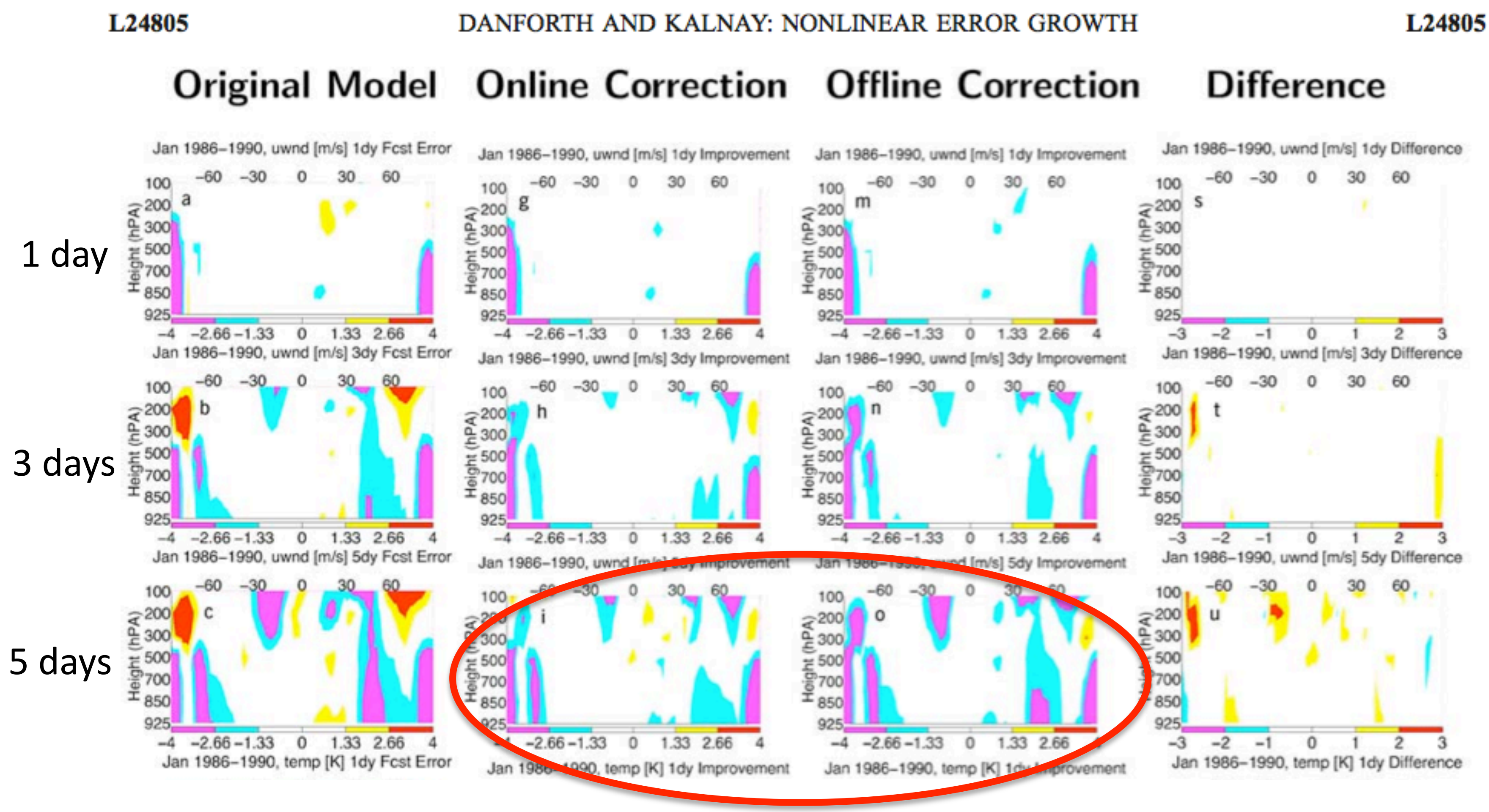
DKM-2007 results

- Estimated the monthly mean 6hr forecast bias
- Corrected the model by adding (–bias/6hr) to each variable time derivative, at each grid point.

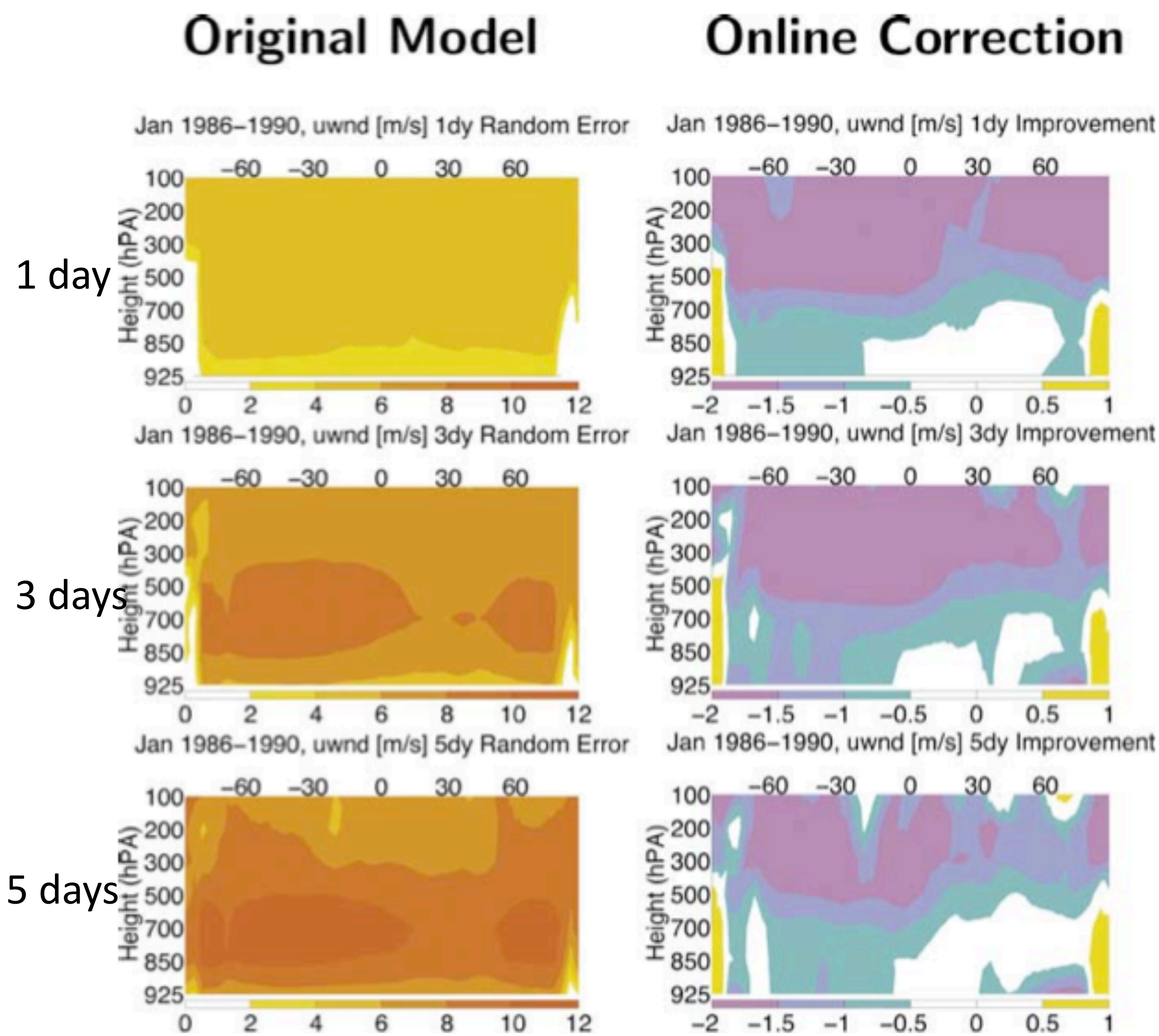
Results

- The bias correction after 3 or 5 days was the same as the best *a posteriori bias* correction.
- But the random errors were **smaller**.
- The dominant EOFs of the 6hr debiased forecast errors were the errors in the diurnal cycle.
- It was possible to estimate the systematic errors for anomalies (e.g., ENSO, lows over land or over ocean)

The model corrected online did at least as well as the model statistically corrected off-line



And the random errors were significantly smaller than in the run without bias correction!

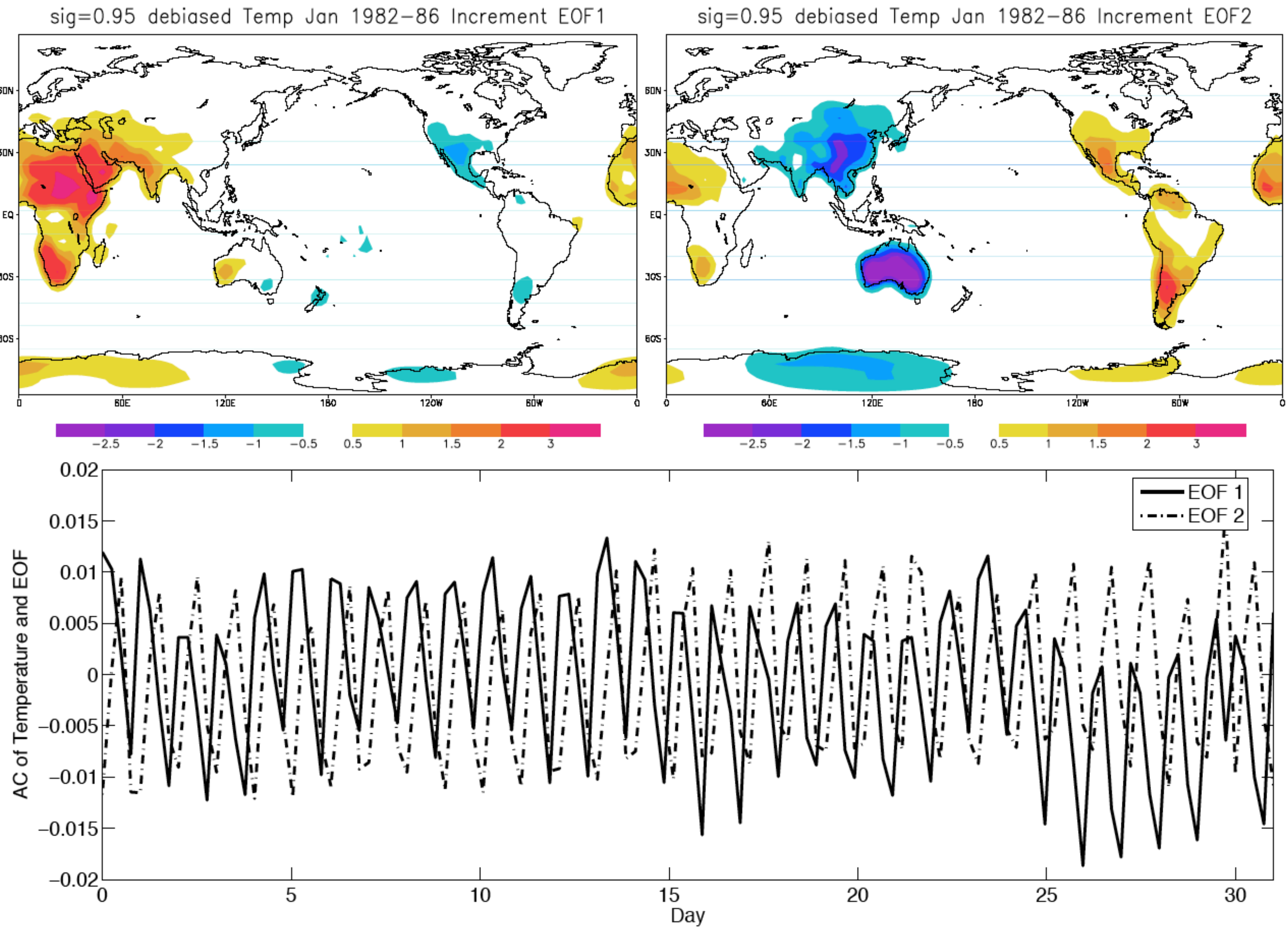


RANDOM ERRORS IMPROVED

How to find the diurnal cycle model errors using EOFs from a Reanalysis (Danforth et al., 2007)

Estimated the average SPEEDY model error (bias) by averaging over several years the 6 hour forecast (started from reanalysis) minus the reanalysis.

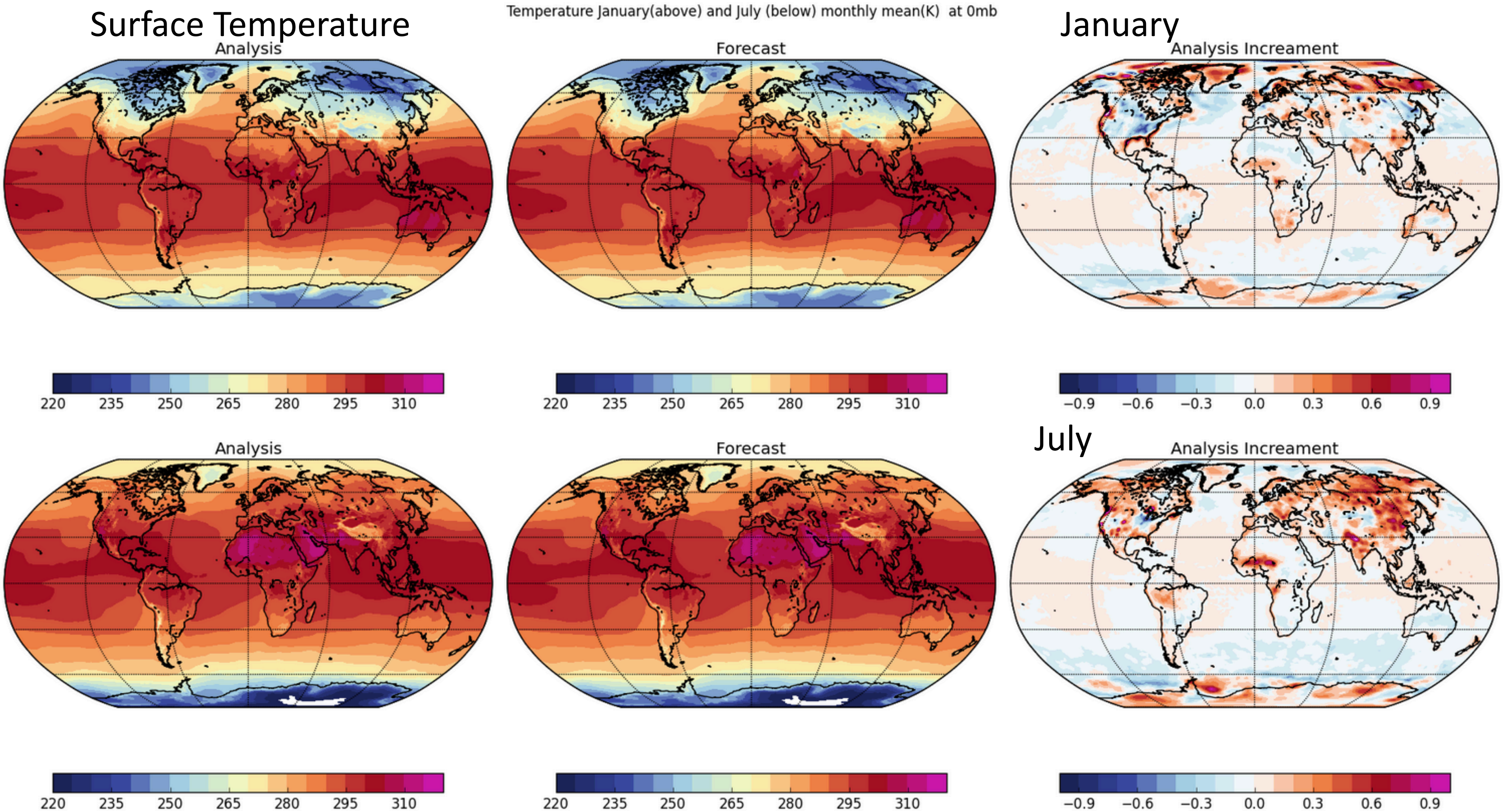
Then they computed the EOFs of the anomaly in the model error, and found two dominant EOFs representing the model error in representing the diurnal cycle:


sig=0.95 debiased Temp Jan 1982-86 Increment EOF1
sig=0.95 debiased Temp Jan 1982-86 Increment EOF2
60N
30N
EQ
30S
60S
0
60E
120E
180
120W
60W
-2.5
-2
-1.5
-1
-0.5
0.5
1
1.5
2
3
EOF 1
EOF 2
AC of Temperature and EOF
Day
0.02
0.015
0.01
0.005
-0.005
-0.01
-0.015
-0.02
5
10
15
20
25
30

Implications for improving the model bias

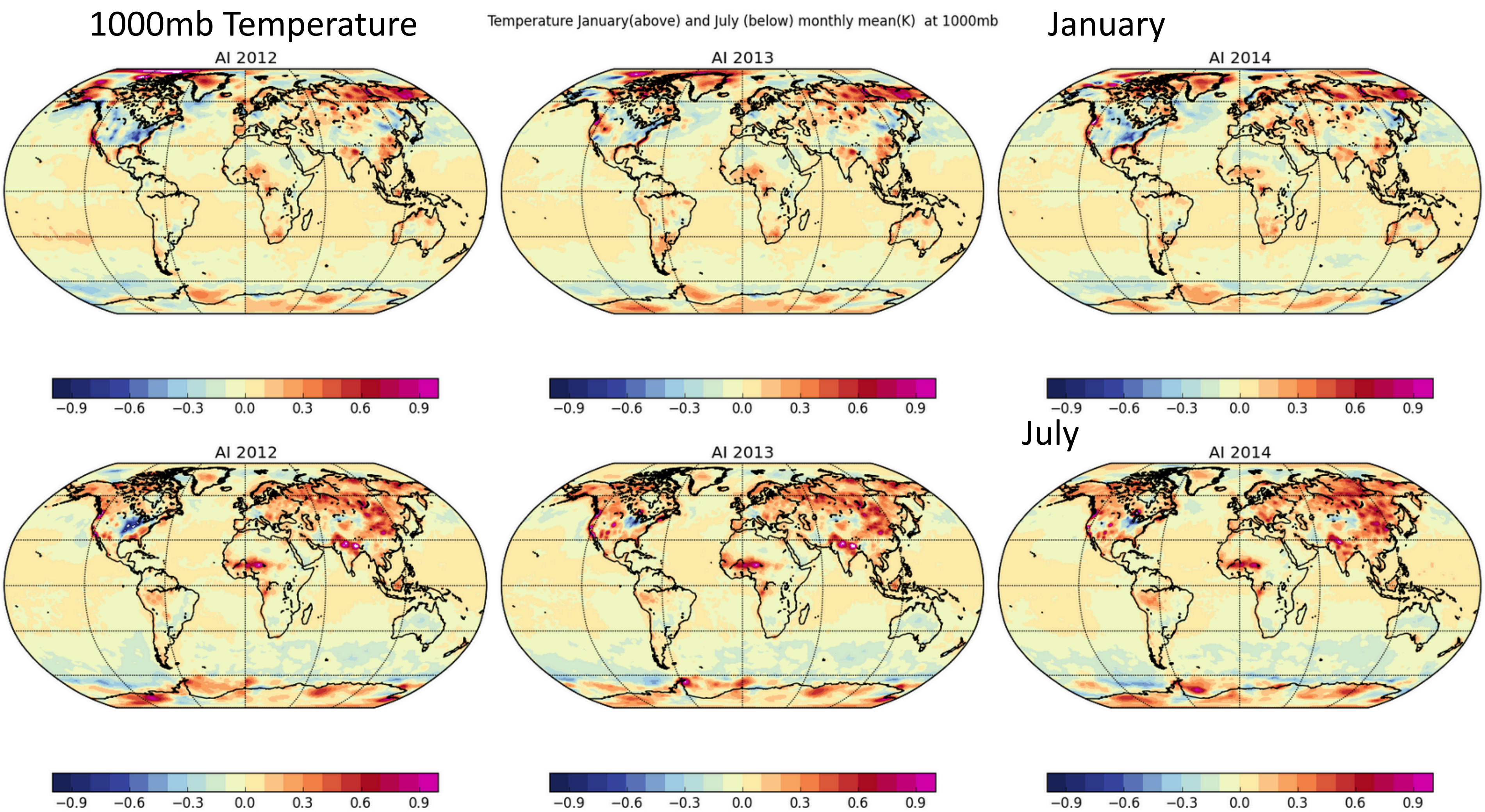
- The DKM2007 method gave very good results with the SPEEDY model, using R1 as an approximation of the true atmosphere.
- The -bias/6hr was added to the SPEEDY time derivatives (u,v,T,p_s).
- This corrected the bias, getting similar or better results than an *a posteriori* bias correction! In addition, random forecast errors were also reduced.
- It was also used to improve the diurnal cycle and to find the state dependent systematic errors (e.g., during an El Niño).
- **It can be tried on the GFS (or the CFS!) taking advantage of the *Analysis Increments*, i.e., the difference between the Analysis and the Forecast.**
- Dr. Fanglin Yang (NCEP) very kindly provided us (Kriti Bhargava, Jim Carton and me) with 2014, 2013, and 2012 Analyses and Forecasts.

First results: 2014 Analyses, Forecasts and AIs

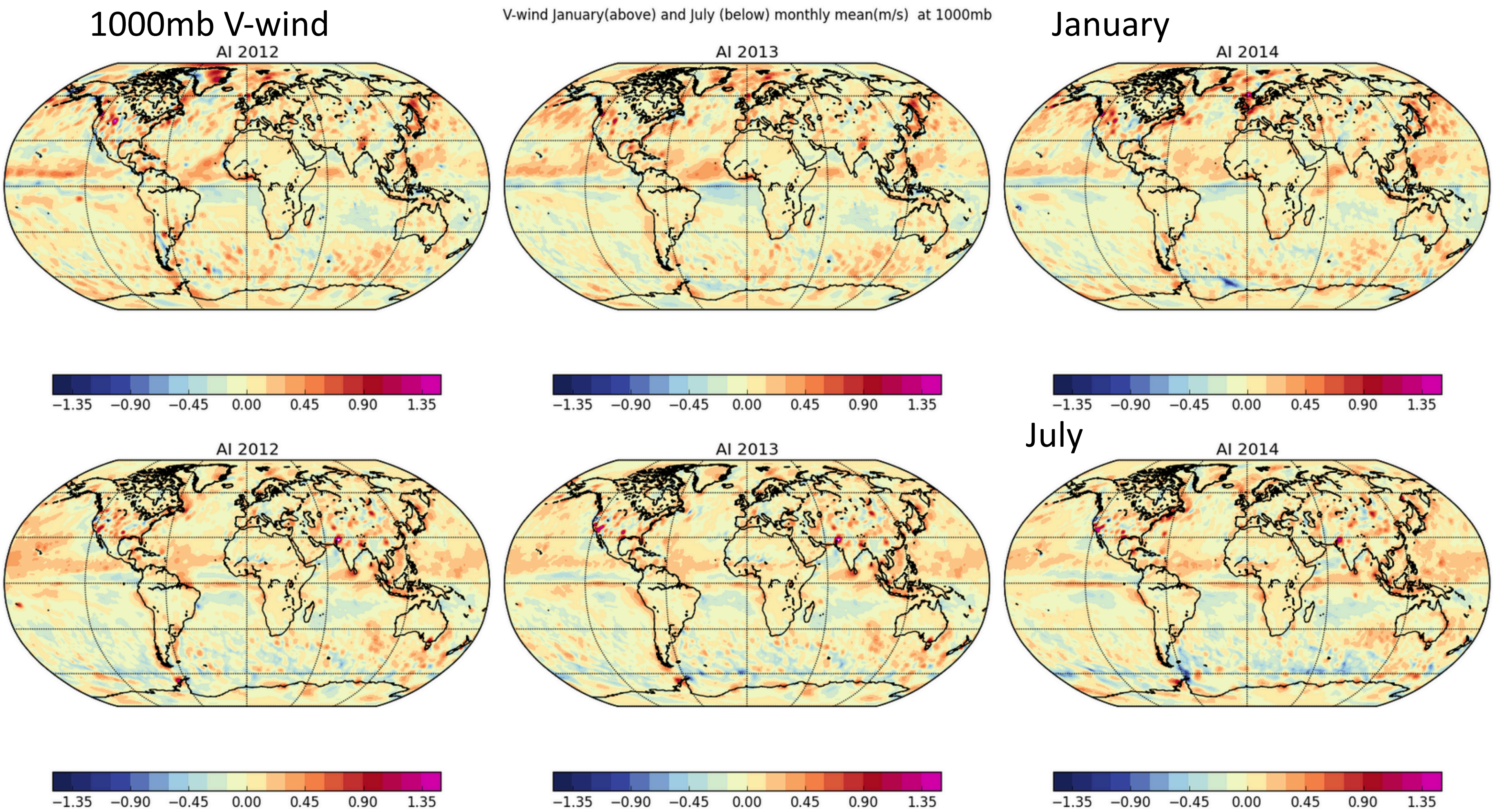


T_s is too low over continents in the summer, too high in the winter.

Analysis Increments: 2012, 2013, 2014



Analysis Increments: 2012, 2013, 2014



How do we proceed to reduce model bias?

- Check the robustness of the monthly average AI (2014 vs. 2013 vs. 2012, July vs. August), earlier years. ✓
- Seasonally filter with 2-3 Fourier time components.
- Perform exploratory low resolution (T254) experiments correcting the perceived model bias by <u>adding AI/6hr to each variable time derivative</u>.
- Test the impact on the forecast skill.
- Explore the diurnal cycle of the AI (error correction). Test if the diurnal cycle errors can be reduced.
- If successful, the AI bias correction will also guide the development of the physical parameterizations.

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THANKS!